GEOBIA at the Terapixel Scale: From VHR Satellite Images to Small Woody Features at the Pan-European Level

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GEOBIA at the Terapixel Scale: Toward efficient mapping of Small Woody Features from heterogeneous VHR scenes

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ABSTRACT. *Land cover mapping has benefited a lot from the introduction of the GEOBIA paradigm, that allowed to move from a pixelwise analysis to a processing of elements with richer semantic content, namely objects or regions. However, this paradigm requires to define an appropriate scale, that can be challenging in a large-scale study where a wide range of landscapes can be observed. We propose here to conduct the multiscale analysis based on tree-based representations, from which features are derived over each single pixel. Efficient and scalable algorithms for tree construction and analysis, together with an optimized usage of the random forest, provide us with a semi-supervised framework in which a user can drive mapping of elements such as Small Woody Features at a very large scale. Indeed, the proposed open-source methodology has been successfully used to derive a part of the HRL product of the Copernicus Land Monitoring service, thus showing how the GEOBIA framework can be used in a big data scenario made of more than 30,000 VHR satellite images representing more than 120 TB of data.*

KEYWORDS: *big data; scalability; multiscale analysis; land cover mapping; differential attribute profiles; random forest; open source*

1. Introduction

While the GEOBIA paradigm has led to significant improvements in the analysis and understanding of remote sensing images thanks to the processing of objects (i.e., regions) instead of pixels (Blaschke, 2010), it still requires to identify the objects (or segment the image into regions) before applying rules for classifying the extracted objects. This segmentation step is not straightforward and relies on user expertise or empirical tuning to be adapted to each new scene to be processed (Dragut *et al.*, 2014; Ming *et al.*, 2015). Thus, it cannot be used for Big GeoData where large-scale analyses require methods that are both very efficient and robust to the wide variety of scenes to be observed.

We address here these multiple issues by relying on a multiscale image representation that embed in a tree structure, with no need of parameter tuning, the different (nested) objects to which a pixel can belong (Bosilj *et al.*, 2018). Computation of such a stack of segmentations benefit from some recent scalable implementations that make realistic their very fast extraction from large-scale image datasets (Havel *et al.*, 2016; Carlinet, Géraud, 2014). Once the tree structure has been extracted, further image analysis is conducted at a very low computational cost, and relies on Differential Attribute Profiles (DAP). These state-of-the-art features (Dalla Mura *et al.*, 2010), or more precisely on only the most relevant features. We benefit from the efficiency of the different steps (tree construction, feature extraction, training, prediction) to propose a semi-supervised strategy (Merciol *et al.*, 2017) where we retrain the model for each kind of landscape, thus allowing to tackle the great variety in appearances of objects at a very large-scale (e.g. VHR imagery at Pan-European scale). Due to the low computational cost (e.g. a few minutes for a Pleiades or WorldView-2/3 scene), a user can then interactively improve the classification by updating the reference samples used for training the model. The proposed scalable solution fully relies on open source components (Orfeo ToolBox, Boost, GDAL, Shark, Triskele OTB remote module) and so can be used in any GEOBIA applications.

To illustrate our methodology, we consider here the Mapping of Small Woody Features (SWF), that is to be included as part of a new High-Resolution Layer (HRL) covering the whole of Europe from Iceland to Turkey within the Copernicus pan-European component of the land monitoring service. SWF represent some of the most stable vegetated linear and small landscape objects providing numerous ecological and socio-cultural functions related to soil and water conservation, climate protection and adaptation, biological diversity and cultural identity. Extracting these objects over such a large area (almost 6 million sq.km) from VHR imagery brings numerous challenges: large amount of data (greater than 120 TB), large number of individual image scenes (greater than 30,000), diversity of the European landscapes, and need to process these data in a timely manner whilst ensuring a satisfactory degree of precision.

This paper is organized as follows. We review the proposed methodology in Sec. 2. The thematic application on SWF mapping is addressed in Sec. 3, where quantitative results are also provided. Finally we conclude the paper in Sec. 4.

2. Method

In this section, we present the proposed methodology with a focus on the overall architecture, before describing in more details the two main components that are feature extraction with attribute profiles and semi-supervised classification.

2.1. Overall architecture

To make the GEOBIA paradigm compliant to very large-scale analysis, we propose here to perform a pixelwise analysis of object-based features, in a semi-supervised classification framework instead of the standard application of GEOBIA rulesets. The overall methodology is given in Fig. 1.

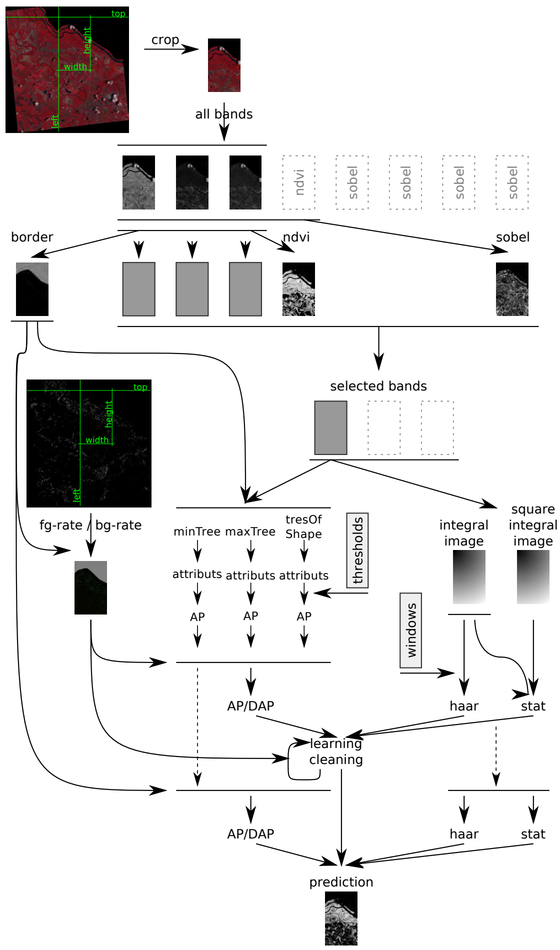

Figure 1. General flowchart of the proposed approach

In a first step, the input image is enriched with the computation of some predefined indices to derive new image channels. Among the considered measures, we rely on the well-known and low-cost NDVI vegetation index as well as the Sobel gradient for texture characterization. While Haralick features are popular to describe texture[1], they are not compliant with very efficient process. We have thus preferred to rely on the Sobel operator, that can be efficiently computed with a set of optimized, 1-D linear convolutions that consists of only 4 computations per pixel. This first step also allows to derive a binary mask that will be useful to discard the no-pixel data in subsequent processing steps.

From the set of selected bands, we then build multiscale representations through the model of morphological trees from which we derive multiscale features called attribute profiles. Such trees can be seen as a stack of nested segmentations and thus a generalization of the concept of monoscale segmentation layer in GEOBIA tools. Each pixel is then assigned with some features derived to the different objects it belongs to in the different scales. Computation of the trees and the attribute profiles is described in more details in Sec. 2.2. Complementary to attribute profiles, we also compute textural features with efficient algorithms based on integral image representations (Viola, Jones, 2001), such as Haar-like features and local statistics (mean, standard deviation, entropy).

The next step is the use of the random forest classifier in a semi-supervised framework. The advantage of using supervised classifier over predefined rulesets is the ability to adapt to a wide range of landscapes without explicit definition of the properties of mapped objects. However, it also requires labeled samples that describe the sought class and the background. Since labeling a full high-resolution image is tremendous, we rather propose a semi-supervised strategy where the training samples are generated by extending the initial sets provided by the user. Given the low computation time of the classification process over the labeled samples, the user can then easily improve the quality of the training set by providing new samples. Once the model is accurate enough, the final prediction is performed. More details are given in Sec. 2.3.

The overall process is very efficient due to a high-level of parallelism in the different steps. The reader interested in the algorithmic details and the optimization of the overall pipeline is referred to a companion paper (Merciol *et al.*, 2017).

2.2. Feature extraction

The GEOBIA paradigm is usually based on some features that are extracted from each single object or region in a segmentation map. Such features describe the object properties such as its shape, spectral and/or textural content, etc. We propose here to rely on attribute profiles that have been very popular image features in remote sensing. The main difference with the standard GEOBIA workflow consists in the fact that the

1. Let us note that in a recent study, we have further shown the interest of measuring attribute profiles over textural features (Pham, Lefèvre, Merciol, 2018).

attribute profiles are measured over each single pixel. One can wonder how such a pixelwise analysis can be compliant with the object-based paradigm. Indeed, while being computed over each single pixel, these features are made from the properties of the objects the pixels belong too in the different segmentations. Feature extraction with attribute profiles can thus be seen as a strategy to derive object-based features in each pixel. It provides a generic framework that allow for robust features that can be extracted in a very efficient way from input images through their modeling into tree-based representations.

There exist different tree models, and we focus here on the inclusion trees, namely min-tree, max-tree, and tree of shapes. These models describe the level sets of an input image, and the nested segmentations are partial (i.e. there could be some parts of an image that do not correspond to any segmented region). A min-tree will highlight the local minima that will correspond to the leaves of the tree. Conversely, a max-tree emphasizes the local maxima in its leaves. These dual representations can be replaced by a self-dual model called the tree of shapes that contain extrema in its leaves. In all cases, the root of the tree is made of the whole image. While we could have also considered partition trees (that would include the standard multiresolution segmentation used in GEOBIA framework), our choice is motivated by the fact that the features extracted from the tree (attribute profiles) have been extensively built from inclusion trees, and their computation from partition trees remains challenging (Bosilj *et al.*, 2017). A recent comprehensive survey on the various tree-based representations is given in (Bosilj *et al.*, 2018).

Once a tree is built, the computation of attribute profiles (Dalla Mura *et al.*, 2010) is as follows. First some attributes are measured within each node. They can be increasing (such as the size) from the leaves to the root, or non-increasing (such as the standard deviation or moment of inertia). Furthermore, they can describe the shape, the heterogeneity, or any other property of the underlying object. A set of thresholds is then defined to filter the tree and retain selected nodes that have attribute values corresponding to the threshold. This step called filtering aims to prune the initial tree to build a very small subset of nodes. Each pixel belongs to a few of them, and can be characterized by their properties (in the standard attribute profile approach, their gray values). Since the filtering may lead to similar images between two successive thresholds, it is often relevant to rely on differential attribute profiles instead of standard attribute profiles. The differential representation is built by computing the difference between two successive values in the filtered tree.

In our scenario, and in order to limit the computational cost, we rely on some efficient implementations of the tree construction and attribute computation steps. Such algorithms have been described in (Merciol *et al.*, 2017) and made available as an open-source library called Triskele[2] that can be used as a remote module in OTB. Furthermore, we limit the computation of the attributes to the subset of pixels relevant in the learning phase.

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2. https://sourcesup.renater.fr/triskele

2.3. Semi-supervised classification

Conversely to the standard GEOBIA methodology that makes use of predefined rulesets to be applied on the objects extracted from a prior segmentation, we rather rely here on a supervised classifier. This choice is motivated by the fact that is it not easy to define an appropriate ruleset for the sought objects, given the context of a very large scale study where the objects appearance might vary a lot from one landscape to the other.

Among the different supervised classifiers available, we have decided to rely on random forest that have shown great success in remote sensing (Belgiu, Drăguţ, 2016). The random forest is an ensemble method (Breiman, 2001) that combines multiple decision trees to increase the robustness of the overall classification process. Each decision tree will operates on a subset of the training samples, with a subset of the available features, and can be used to derive a prediction from an input instance. The set of individual predictions can then be gathered through a majority voting procedure.

The random forest classifier is known to be easy to tune with only a few parameters to be set, namely the number of trees in the forest (usually 100, 200 or 500), and the number of random variables used in each tree (usually set as the square root of the feature vector length). Furthermore, it comes with parallel, scalable, open-source implementations such as the Shark library[3]. We use here this library, that has been also recently embedded into the OTB framework[4].

Another advantage of the Random Forest classifier is its ability to measure the importance of the different features. Indeed, it is possible to identify the role of each individual feature in the ensemble method (in other words, how many times it has been used to derive the prediction). We thus allow the user to select the appropriate features when dynamically adapting its training set. With a lower number of more discriminant features, we both achieve higher accuracy and lower computational cost.

As already indicated, we consider here the random forest classifier in a semi-supervised framework. From the labeled samples provided by the user to characterize foreground (class of interest) and background (other classes), we only consider a random subset (defined by fg_rate and bg_rate parameters) of them to limit the computation time. In order to alleviate the negative effect brought by errors in the training set, we also allow to discard positive samples that led to a low classification accuracy. Besides, the background set has to be heterogeneous to adequately represent all classes in the scene but the sought one. While the user can provide such samples, it barely corresponds to all background classes. Thus, we allow for automatic selection of background pixels among those that the random forest classifier assigns to the sought class with a very low confidence.

3. http://image.diku.dk/shark
4. https://www.orfeo-toolbox.org

Thanks to the low computational time of the random forest learning step, it is possible for the user to judge the quality of the prediction over the training set, and to adapt the content of the set if necessary. Once the prediction model is satisfactory, it can be applied over the whole image to get the final map.

3. Application

3.1. Context

Small Woody Features (SWF) represent some of the most stable vegetated linear and small landscape features providing numerous ecological and socio-cultural functions (Forman, Godron, 1981; Van der Zanden *et al.*, 2013; Jongman, 2004). Although a single linear feature cannot ensure all these functions on its own, SWF are ecologically significant, structural landscape elements that act as important vectors of biodiversity and provide vital habitats and ecosystem services. Hedgerows and tree groups are linked to landscape richness and fragmentation of habitats with a direct potential for restoration while also contributing to hazards protection and Green Infrastructure, amongst others. The specific ecological importance of SWF underpins the need for reliable, detailed geospatial information on the occurrence and distribution of linear landscape features. SWF are an elementary part of a landscape's green infrastructure and are therefore addressed through a range of policies and directives. EU's 2020 Biodiversity Strategy and specifically its Target 2 with regard to ecosystem maintenance, restoration and the establishment of a green infrastructure, clearly expresses the requirement for systematic monitoring of such features being crucial for ecosystem condition and the delivery of ecosystem services.

In past years, remote sensing has been increasingly acknowledged to provide objective and cost-efficient approaches for mapping of small landscape elements, however, there is still no consistent inventory of SWF throughout Europe. Through initiatives such as Coordination of information on the environment (CORINE) Land Cover, and even more since the start of Copernicus and its Initial Operations with the High Resolution Layers (HRL) and the Urban Atlas, Europe has significantly improved its knowledge base on land cover/use and vegetation patterns based on EO data. While the overall landscape heterogeneity is defined by the spatial arrangement of homogeneous land cover patches, as measured by the Copernicus continental land monitoring component, its interconnections are constituted by linear structures that portray the joint role of nature and mankind in shaping the countryside (Turner, 1989). Both the spatial arrangement of land cover and the presence of linear structures are the two most relevant elements characterizing landscape structures. Geospatial information on SWF is however still lacking and only available in the form of limited national investigations mostly with a focus on farmland features (Jongman, Bunce, 2009) or other thematically focused small-scale landscape inventories, e.g., fragmentation studies such as (Jaeger *et al.*, 2008).

The only quantitative information on pan-European level is available through ground observations from the LUCAS (Land Use/Cover Area frame Statistical survey) database

(Eurostat, 2009). Recent studies such as (Van der Zanden *et al.*, 2013) have derived density maps of the spatial distribution of linear landscape elements for Europe based on spatial interpolation of LUCAS data, but the resolution of such information (1 km) is too coarse for detailed assessments and does not provide factual quantitative information on their location and extent.

As part of the pan-European Copernicus Land Monitoring Service, the High Resolution Layers (HRLs) provide maps of multi-temporal land cover characteristics for 5 thematic areas including SWF in a consistent manner for 39 European countries (EEA39 with more than 6 million sq.km). SWF is a completely new product as part of HRLs for the 2015 reference year, which is based on extended demonstrated expertise in the production of HRLs at Pan-European level (Lefebvre *et al.*, 2013) and with dedicated exploratory work specifically on SWF (Lefebvre, 2014). The mapping of SWF is using Very High Resolution (VHR) data as primary input with a pan-European coverage as well as in-situ data. The VHR_IMAGE_2015 dataset made available in the ESA Copernicus Data Warehouse (DWH) is the main data source for the detection of Small Woody Features identifiable within the given image resolution ($\leq$ 1m panchromatic, 2-4m multi-spectral). This dataset includes more than 30,000 VHR images which corresponds to more than 120 TeraBytes of data.

The main difficulty when dealing with VHR images comes from the internal variability of the information for a single land-use. For instance, woody elements are represented by a high number of heterogeneous pixel values hampering usual pixel-based techniques. Nevertheless, even though object-based image analysis (OBIA) appears to be the most suitable approach to delineate SWF with VHSR images, it can potentially represent some serious drawbacks related to the heterogeneous size and shape of SWF objects and the difficulty to determine suitable segmentation parameters (Fauvel *et al.*, 2013). In addition, for very small objects close to the resolution of the imagery, the segmentation can lead to separate SWF or non-SWF objects to be merged together due to mixed pixel values. This makes it particularly difficult to define a suitable segmentation scale in different landscapes particularly if it is to be applied for the EEA39 area. Therefore, a multi-scale approach conducted both at pixel and object level is suggested to ensure the correct identification of small and irregular shaped SWF (pixel based) and larger SWF (OBIA) such as small patches of trees or scrub or larger hedges.

3.2. Automatic classification

A dedicated processing chain has been developed and implemented in order to process large dataset of VHR images ($> 30,000$ scenes) to produce the SWF layer. The workflow is shortly described as follows: (1) VHR Image Pre-processing, (2) Reference database preparation, (3) Automatic classification, (4) Post-processing, (5) Thematic manual enhancement and (6) Internal Validation.

The proposed paper focuses on the automatic classification step, a supervised classification, which classifies each VHR image into woody and non-woody vegetation.

The overall methodology to produce such a map has been provided in Sec. 2. We recall that it proceeds in two steps. In a first step, feature extraction is achieved through a novel, efficient implementation of differential attribute profiles (DAP) that are among the state-of-the-art image descriptors in remote sensing. In a second step, SWF are extracted in a semi-supervised context using an open source implementation of the popular Random Forests classifier. Besides demonstrating the strength of open source software for helping the large-scale production of land cover maps, we also introduce several new developments related to the DAP features. Those features are straightforwardly extracted from a prior tree-based, multiscale representation of the image. They allow to gather both spectral and spatial information in an efficient manner.

3.3. Experiments

3.3.1. Data

The proposed strategy has been applied and evaluated on a dataset covering two study sites, one in Romania (Large Region 9—LR09) and one in Germany (LR61). The dataset contains 37 VHR images in total which covers respectively about 7,000 and 10,200 sq.km. The images were acquired by different satellites, Pleiades and WorldView, but all scenes include 4 spectral bands (Blue, Green, Red and Near-InfraRed) and have 2m spatial resolution. The area covered by the images varies from 192 to 1223 sq.km (ca. 48 to 306 Mpixels).

3.3.2. Results

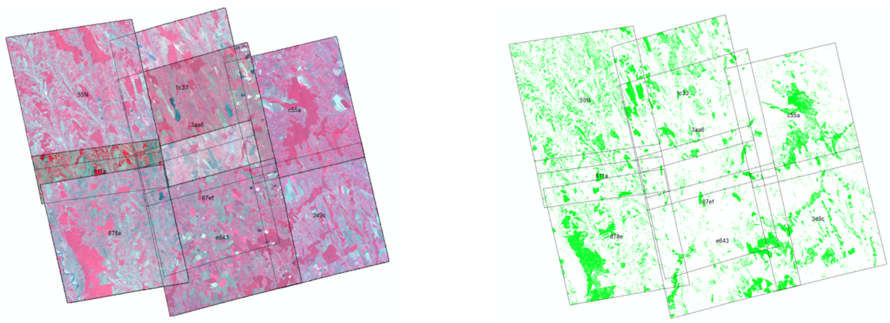

Figure 2. VHR images (left) and corresponding classification results (right) over the Romanian site (LR09)

Figure 2 shows the results of the classification over the Romanian site, with a close-up given in Fig. 3. The automatic classification was applied based on reference database extracted from several land cover datasets including the Copernicus HRL Tree Cover Density Layer (TCD), the Riparian Zone and Natura 2000 from the Copernicus Local components and LUCAS database. The classification is trained on 70% of the reference sample dataset and the remaining 30% are used for the accuracy assessment in order to derive the accuracy figures.

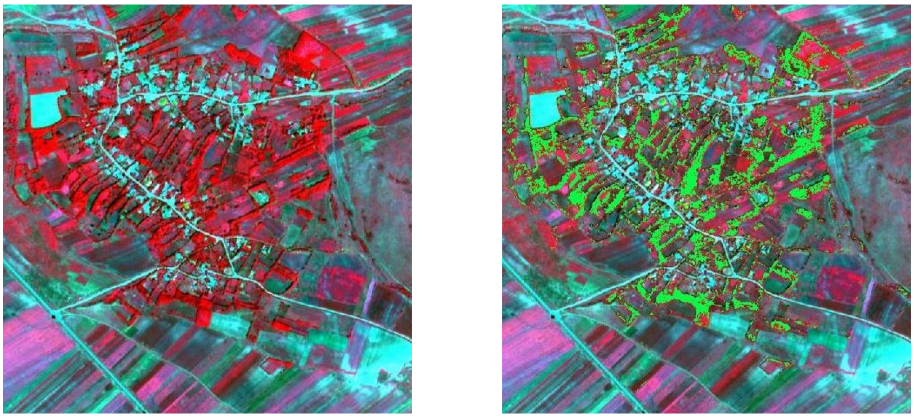

Figure 3. Sample of the VHR image (acquired by 21/07/2014) (left) and corresponding classification results (right) over the Romanian site (LR09)

Given the operational purpose of the tool, the combination of fast processing time and high classification accuracy is essential. Tables 1 and 2 show the classification results for each analysed VHR image in terms of processing time and classification accuracies. The computing time is based on a dedicated server infrastructure with high computing capabilities (Bi-CPU Xeon, 24 cores). Whereas the processing time for classifying a Pleiades image (training + classification) on the Romanian site is around 5 minutes, this time is double for the Worldview images on the German site which cover around twice the Pleaides area (481 versus 867 sq.km). Given such reasonable processing times, a Large Region of about 40,000 sq.km can be processed within one day considering an image overlap of about 50%.

The classification quality is measured by the Producer Accuracy (P.A., related to the omission errors) and the User Accuracy (U.A., related to the omission errors). The number of reference pixels gives an indication of the confidence of the accuracy figure (low reference number means less confidence). On Romanian site (Table 1), the P.A. ranges from 77 to 99% whereas U.A. from 83 to 100%. The average P.A. and U.A is respectively 89.4% and 95.7%. On German site (Table 2), the P.A. ranges from 84 to 95% whereas U.A. from 75 to 99%. The average P.A. and U.A is respectively 89.9% and 91.4%. For both sites, the classification accuracy is high (>80%) even if the accuracy figures are slightly higher for the Romanian site. This can be explained by the higher commission errors due to highly vegetated agricultural fields on the German site.

Table 1. List of the 20 analysed Pleiades VHR images covering the Romanian study site (LR09) with their characteristics (identifier, acquisition date, and covered area), classification processing time and accuracies (P.A. as Producer Accuracy, U.A. as User Accuracy and # as number of references for each validation)

ID	Date	Area (sq.km)	Time (m:s)	P.A. (%)	U.A. (%)	# P.A. nbpix	# U.A. nbpix
3aa6	29/06/2014	553.6	07:57	92.1	93.4	20,734	6,861
e643	29/06/2014	534.0	07:04	95.6	97.2	17,549	6,888
c514	20/08/2014	404.6	05:52	82.7	100.0	21,634	1,015
55f4	02/06/2015	537.6	04:11	92.3	95.4	28,082	2,564
811a	02/06/2015	192.1	01:21	98.8	86.3	7,392	1,335
1524	02/09/2015	348.1	03:05	82.0	99.6	45,900	778
32bd	02/09/2015	427.7	03:36	88.3	100.0	45,429	79
6390	02/09/2015	437.1	03:31	90.7	100.0	23,952	1,175
94a2	12/07/2016	1,141.7	09:56	79.7	85.5	247,163	159
d34e	30/06/2014	501.7	04:11	87.0	96.8	55,706	1,338
2b88	30/06/2014	418.2	03:43	79.5	92.6	33,250	766
9fc6	30/06/2014	531.0	04:26	91.3	99.5	29,621	4,206
3d9c	21/07/2014	435.4	04:07	94.3	99.2	20,730	392
c55a	21/07/2014	443.2	05:04	97.7	99.1	17,806	4,620
878e	05/06/2015	465.3	04:48	94.9	83.0	26,114	5,775
8ac0	06/08/2015	474.9	06:24	77.3	100.0	85,776	78
d3e6	06/08/2015	416.7	05:11	79.6	100.0	43,288	467
ed14	27/08/2015	412.2	04:20	93.5	99.3	37,394	4,080
1c33	03/09/2015	489.9	05:00	93.6	95.0	23,404	6,031
87ef	03/09/2015	470.4	04:25	96.6	92.4	14,445	7,404
	Average	481.8	04:54	89.4	95.7	42,268	2,801

Table 2. List of the 17 analysed Worldview-2/3 VHR images covering the German study site (LR61) with their characteristics (identifier, acquisition date, and covered area), classification processing time and accuracies (P.A. as Producer Accuracy, U.A. as User Accuracy and # as number of references for each validation)

ID	Date	Area (sq.km)	Time (m:s)	P.A. (%)	U.A. (%)	# P.A. nbpix	# U.A. nbpix
39CC	07/06/2014	1,190.5	11:38	87.7	91.4	249,204	61,635
9A7B	11/06/2015	751.1	06:50	87.8	88.5	30,456	3,893
CBAA	02/07/2015	998.2	09:44	89.5	90.4	45,596	7,187
4DBA	02/07/2015	1,036.3	10:08	91.2	94.8	32,568	11,106
03CA	05/07/2015	1,148.0	11:27	85.5	87.5	44,715	3,057
D92F	05/07/2015	804.5	08:08	84.5	91.0	46,920	3,174
D98A	05/07/2015	809.5	07:41	92.5	90.4	33,555	1,960
400B	13/08/2015	771.0	06:32	93.2	94.9	36,841	2,574
965F	13/08/2015	1,079.8	10:33	92.8	93.9	36,861	3,421
7C04	01/06/2016	659.4	07:19	85.1	75.4	29,975	2,435
E0EA	01/06/2016	1,223.5	13:29	84.8	87.5	185,722	22,349
D7B9	04/06/2016	665.6	06:37	94.8	99.3	32,835	724
837C	26/08/2016	1,048.7	10:19	91.1	91.2	57,338	2,181
97C4	31/08/2016	507.1	05:10	94.2	96.8	71,879	47,140
CF66	09/08/2015	170.6	02:00	95.1	96.4	22,440	23,690
C878	22/08/2015	919.9	09:23	90.1	93.4	158,773	72,212
D84C	22/08/2015	959.4	10:00	89.1	91.3	87,053	21,658
	Average	867.2	08:38	89.9	91.4	70,749	17,082

4. Conclusion

In this paper, we have presented a use case where the GEOBIA methodology has been conducted at a very large scale, i.e. over more than 30,000 scenes and 120 TB. To address the wide range of landscapes encountered at the pan-European scale, we propose to rely on multiscale image representations known as morphological trees such as min-tree, max-tree or tree of shapes. Once built, such representations allow to efficiently derive some image feature that are fed into a random forest classifier. Thanks to the low computational cost of all the individual steps of the overall process (tree construction, feature extraction, supervised learning and prediction), it is possible to have the user in the loop, to updated the classification model and assess the produced results. The presented methodology has been validated on a very large scale use case, namely the mapping of Small Woody Features for the High Resolution Layers product of the Copernicus Land Monitoring service. Our work shows that the concepts of GEOBIA can be employed at a very large scale, if adequate efficient tools and representation models are used.

We consider now to build upon this work and include more advanced features such as local-feature attribute profiles (Pham, Lefèvre, Aptoula, 2018b) or feature profiles (Pham, Lefèvre, Aptoula, 2018a). Indeed, the framework of attribute profiles has benefit from many recent developments (Pham, Aptoula *et al.*, 2018) that still need to be validated on large-scale experiments.

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